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A Machine Learning Assisted Development of a Model for the Populations of Convective and Stratiform Clouds

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Overview

Informed by radar observations and companion cloud-permitting model simulations, we make use of machine learning to develop a model for the evolution of populations of convective cells and their associated stratiform area. We focus on characterizing the interactions between convective and stratiform clouds. Such coupling is an important parameterization issue (e.g. the convective source term in PC2) and the model may also be valuable to inform nowcasting projections.

Data

We use 15 seasons (157,032 frames) of C-POL radar reflectivity data from Darwin, Australia covering (150km)^2 every 10 min. The Steiner et al (1995) algorithm distinguishes convective cells from the stratiform area.

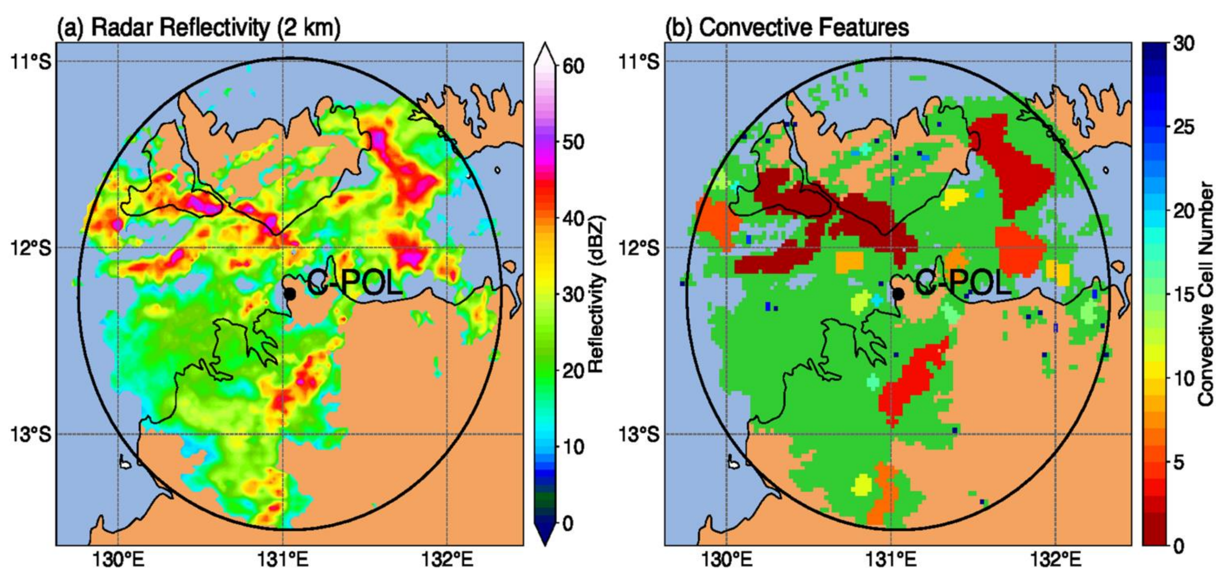

Figure 1. Example radar reflectivity snapshot from the C-POL radar (left) and its decomposition (right) into convective cells embedded in a stratiform region.

Model and learning method

The stratiform area s and convective cell size distribution $\mathbf{c}$ evolve according to

$$\frac{ds}{dt} = f_s(\boldsymbol{c}) - \frac{s}{\tau_s}$$

$$\frac{d\boldsymbol{c}}{dA_c} = f_c(s, \boldsymbol{c})$$

where $A_c = \sum \boldsymbol{c}$ is the total convective area. Machine learning is used to obtain f_s, f_c and τ_s with the C-Pol data providing snapshots of $\mathbf{c}$, s, $\Delta\mathbf{c}$ and Δs.

A single-layer machine learning model is constructed in which the transition functions are defined by weight arrays and bias vectors that minimize the mean square difference between predicted and true $\Delta\mathbf{c}$ and Δs. The code was written in TensorFlow, with an ADAM optimization.

To apply the above model, the total convective area is assumed to evolve as

$$\frac{dA_c}{dt} = \frac{1}{\overline{m_b}}\left(F - \frac{M_b}{\tau_c}\right)$$

which is supported by the cell population model discussed by Hagos et al (2018). F is the forcing, $\overline{m_b}$ and τ_c are constants, and M_b is the total cloud base mass flux, which has contributions from each convective cell obtained using a piecewise linear relationship to the cell area fitted from companion convection-permitting model simulations.

A look at $f_s(\boldsymbol{c})$

The stratiform growth rate increases with convective area fraction and is larger for many small cells rather than a few large cells. Its behaviour can be understood as resulting from hydrometeors being detrained through the perimeters of the convective cells.

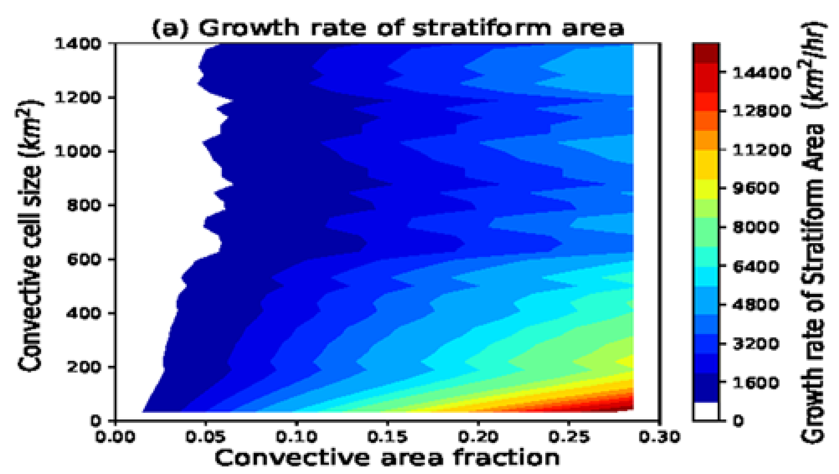

Figure 2. The stratiform area growth rate plotted as a function of the total convective area (horizontal axis), and taking the area to be divided into cells with a given mean area (vertical axis).

A look at $f_c(s, \boldsymbol{c})$

We can assess the effects of stratiform cloud on the convective cell population by looking at the change in population due to disabling the s dependence of $f_c(s, \boldsymbol{c})$. We set it instead to $f_c(0, \boldsymbol{c})$. Stratiform feedback favours smaller cells for a given convective area.

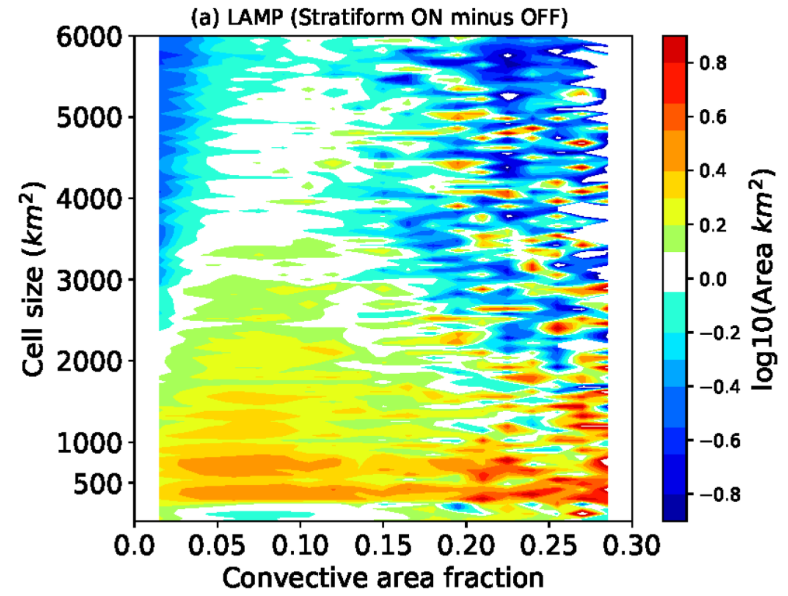

Figure 3. The change in the convective cell population produced by the model. The difference is taken between the model with the full function f_c and that with the restricted function $f_c(s=0, \boldsymbol{c})$. Analyses with restrictions to other constant values of s lead to qualitatively similar results.

Tests with imposed forcings

We now integrate the derived model with imposed forcings F. First we take a constant mean forcing but with a random element also applied in order to demonstrate how the character of the interactions embodied in f_c and f_s affects the maintenance and nature of an equilibrium cloud distribution. We find that stratiform feedback does not affect the total convective area but it does change the distribution as above. It also increases the stratiform area and is important for convective variability, as it acts to dampen large fluctuations in the cell size distribution.

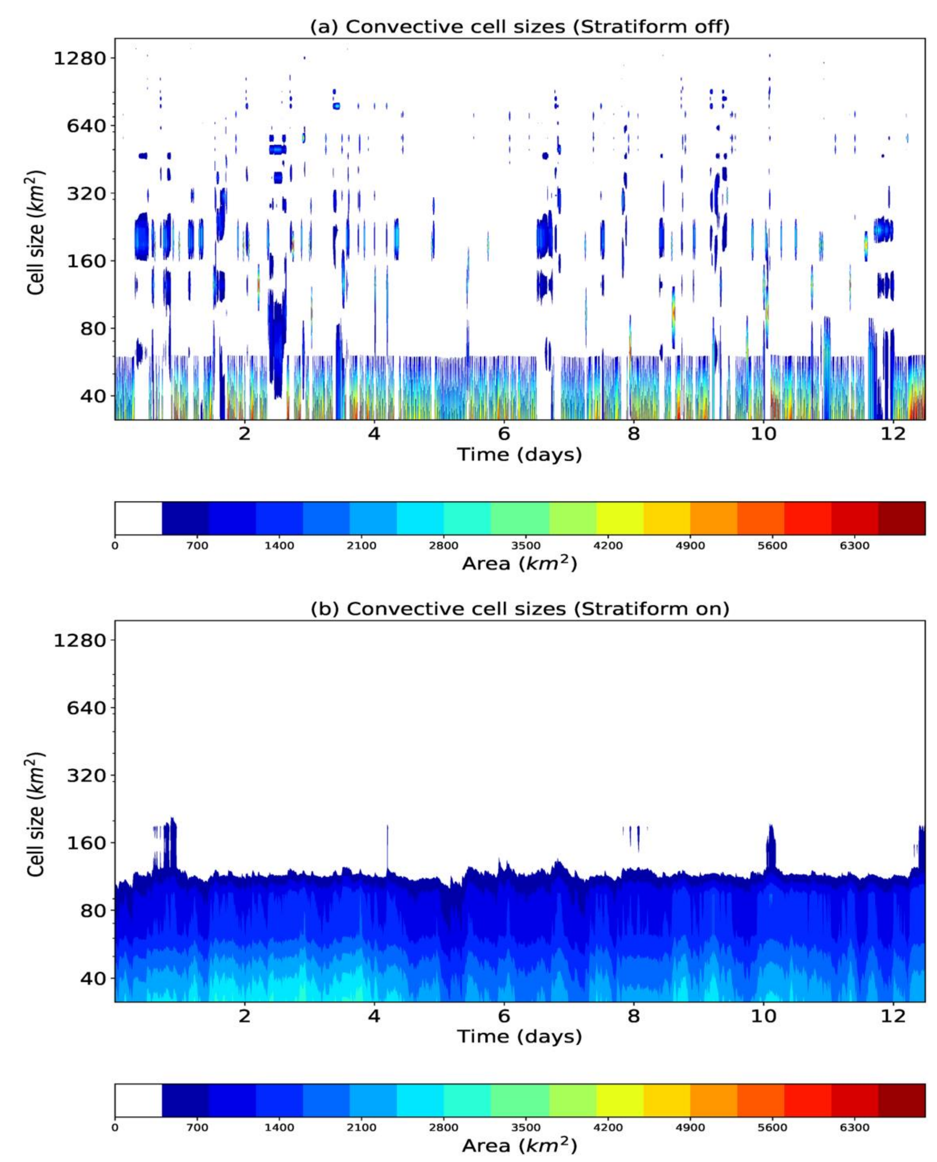

Figure 4. Timeseries of the convective cell size distribution when driving the model with a randomly-fluctuating forcing with constant mean. Results are shown for the restricted function $f_c(s=0, \boldsymbol{c})$ (top) and for the full function f_c (bottom).

Using a half-sine wave forcing to mimic the diurnal cycle over land the strong moderating effect from the stratiform-convective interactions is again apparent in the convective variance. The interactions are also important in order to capture the timing of the diurnal cycle in stratiform area.

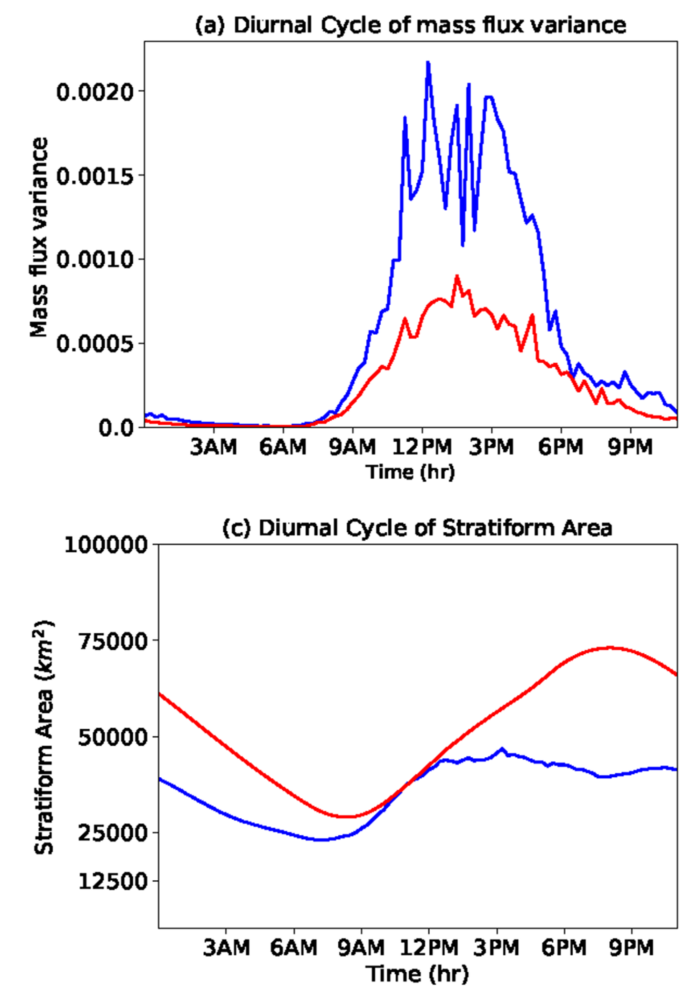

Figure 5. Diurnal cycle of mass flux variance (top) and stratiform area (bottom). Results are shown for the restricted function $f_c(s=0, \boldsymbol{c})$ (blue) and for the full function f_c (red).

Conclusions

- Machine learning can be used to build a model showing the interactions between convective and stratiform cloud.
- A large number of small convective cells is favourable for stratiform area growth
- In turn, stratiform cloud feedbacks favour smaller convective cells and acts to dampen convective variability.
- The model has been devised with a view towards implementation as a parameterization, and some tests are underway by ZH in WRF.

References

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